Using Embeddings to Understand the Variance and Evolution of Data Science Skill Sets

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Jobs are hard to categorize

Research Analyst

Entry-Level

DRG - New York City

We are seeking a Research Analyst to join our team which serves our pharmaceutical clients with actionable data. As a Research Analyst, you will provide data support for client-facing platforms, presentations, and client requests...

Research Analyst

Senior

MMP - New York City

We have an exciting opportunity for an individual to join MMP's Cyber Risk Group. The successful candidate will have the ability to shape our investors service strategy, analytic, research and outreach framework for cyber risk and its relationship to credit and the financial markets...

Research at TapRecruit

Helping companies make fairer and more efficient recruiting decisions

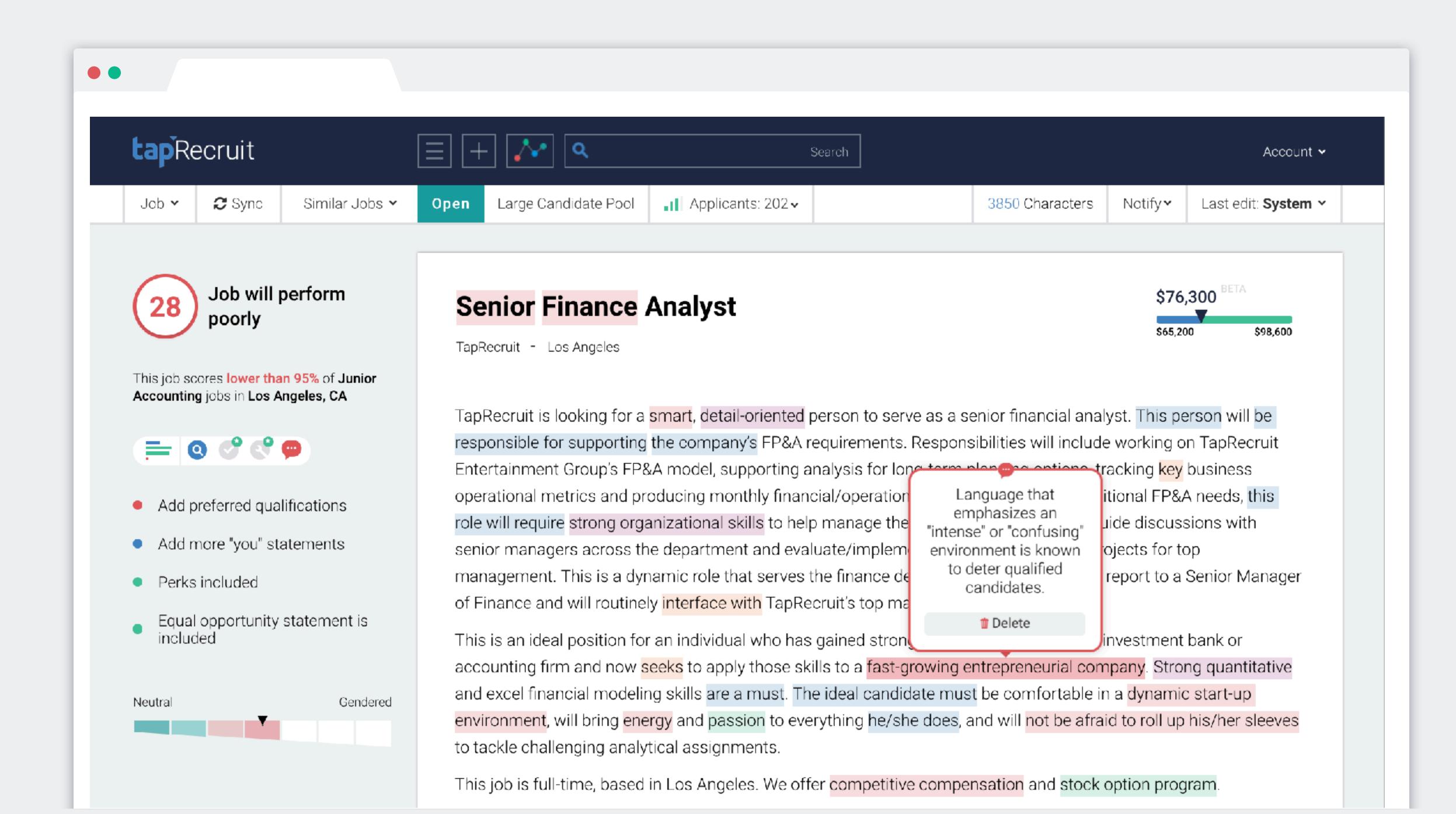
NLP and Data Science:

- What are distinguishing characteristics of successful career documents?
- What skills are increasingly important for different industries?

Decision Science:

- How do candidates make decisions about which jobs to apply to?
- How do hiring teams make decisions about candidate qualifications?



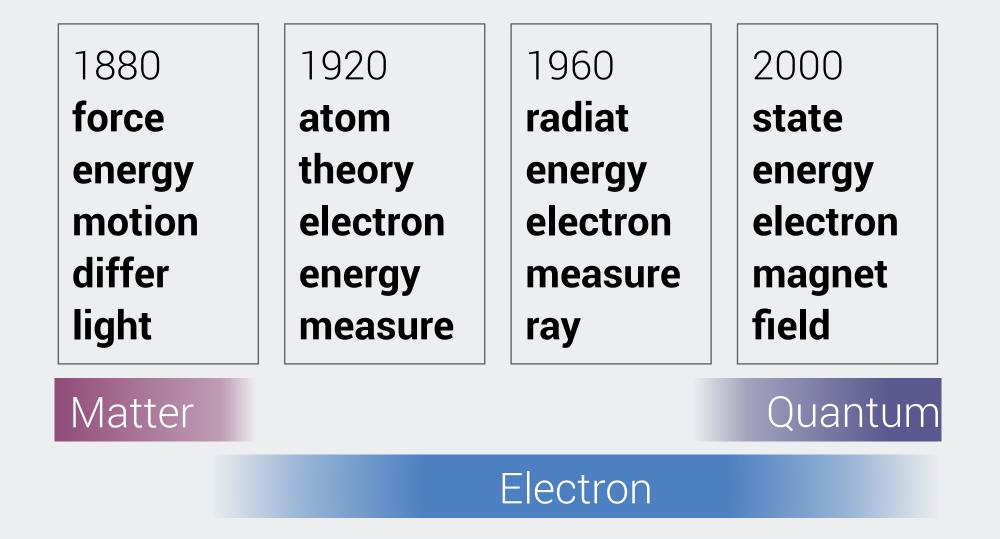


How have data science skills changed over time?

Strategies to identify changes in texts

Traditional approaches do not capture syntactic and semantic shifts





Manual Feature Extraction

Require selection of key attributes, therefore difficult to discover new attributes

Dynamic Topic Models

Require experimentation with topic number



Embeddings use context to extract meaning

Window sizes capture semantic similarity vs semantic relatedness

Statistical modeling through software (e.g. SPSS) or programming language (e.g. **Python**)

Context

Word

Experience in **Python**, Java or other object-oriented programming languages

Context

Context

Proficiency programming in **Python**, Java or C++.

Context

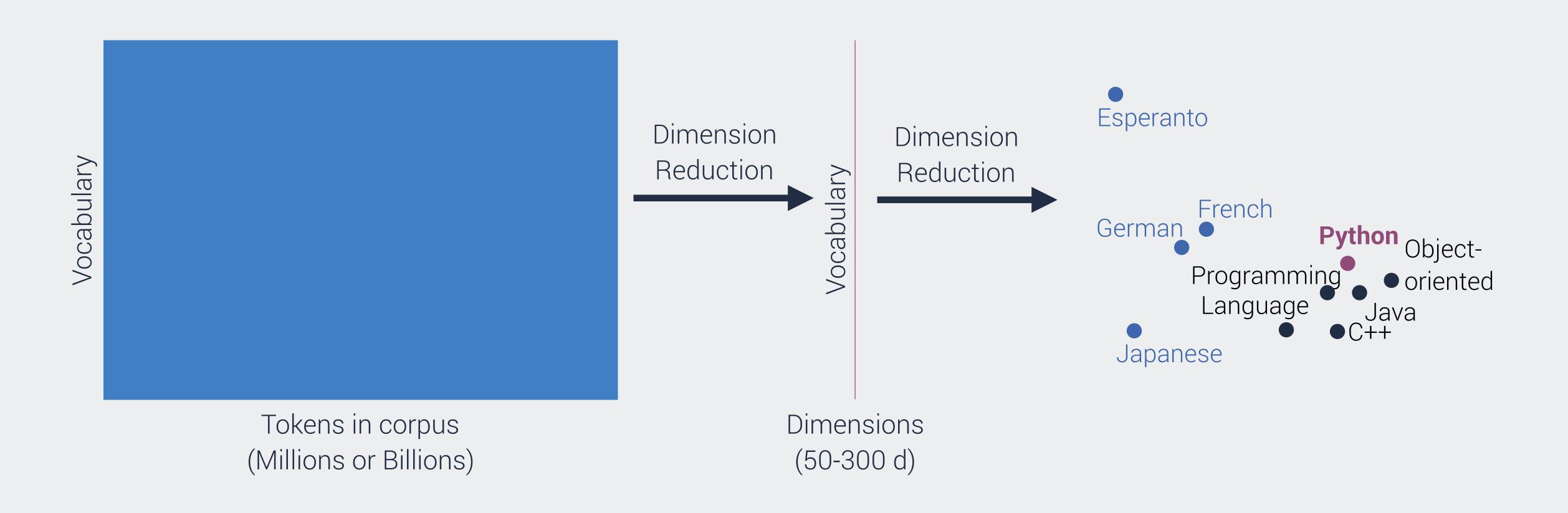
Word

Context



A simplified representation of word vectors

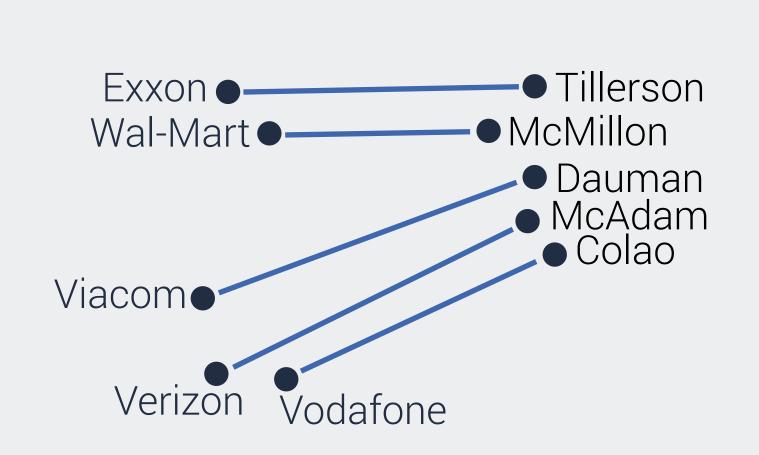
Dimension reduction is key to all types of embeddings models

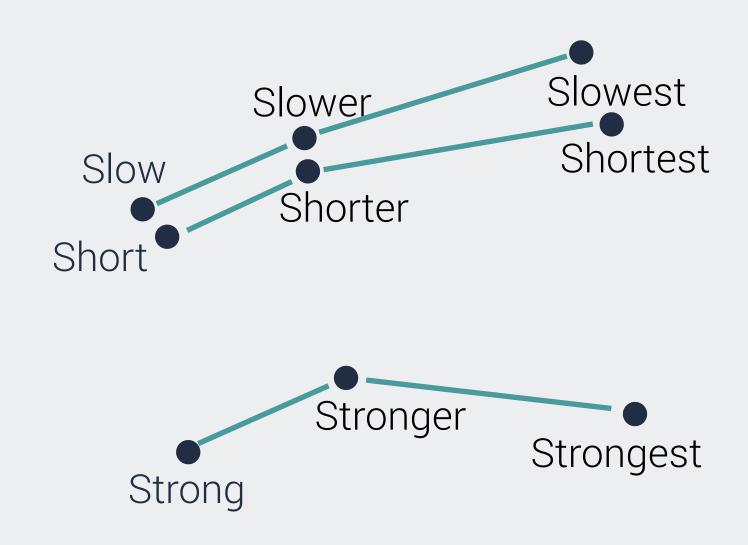


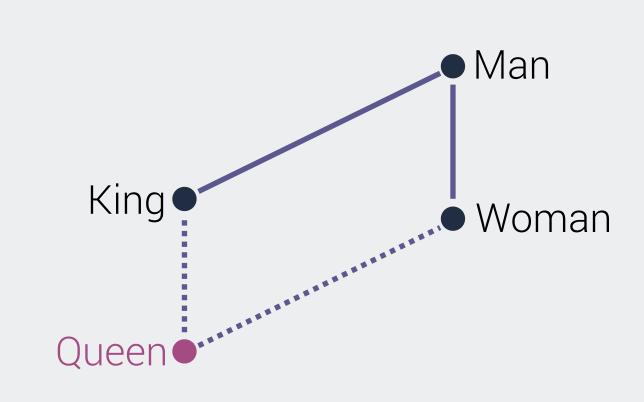


Embeddings capture entity relationships

Dimensionality enables comparison between word pairs along many axes







Hierarchies

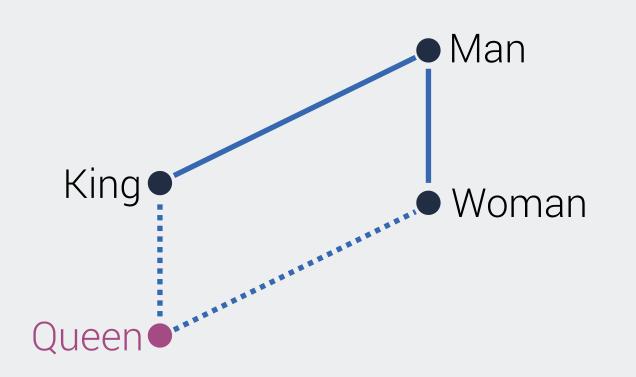
Comparatives and Superlatives

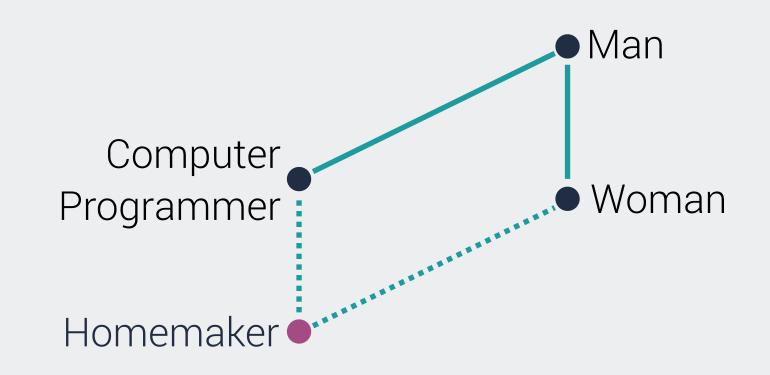
Man :: King as Woman :: ?



Embeddings reflect cultural bias in corpora

High dimensionality enables some bias reduction





Man :: King as Woman :: ?

Man :: Programmer as Woman :: ?



Pretrained embeddings facilitate fast prototyping

Embeddings training should match corpus that is being tested on

Corpus Generation	Corpus	Twitter	Common Crawl	GoogleNews	Wikipedia
	Tokens	27 B	42-840 B	100 B	6 B
Corpus Processing	Vocabulary Size	1.2 M	1.9-2.2 M	3 M	400 k
Language Model	Algorithm	GLoVE	GLoVE	word2vec	GLoVE
Generation	Vector Length	25 - 200 d	300 d	300 d	50 - 300 d
Language Model Tuning Final Application					



Problems with pretrained embedding models

Casing	Abbreviations vs Words e.g. IT vs it		
Out of Vocabulary Words	Domain Specific Words & Acronyms		
Polysemy	Words with multiple meanings e.g. drive (a car) vs drive (results) e.g. Chef (the job) vs Chef (the language)		
Multi-word Expressions	Phrases that have new meanings e.g. Front-end vs front + end		

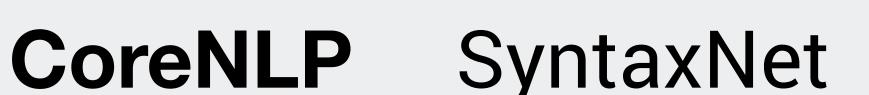


Custom language models tools

Modularized for different data and modeling requirements









Tokenization, POS tagging, Sentence Segmentation, Dependency Parsing









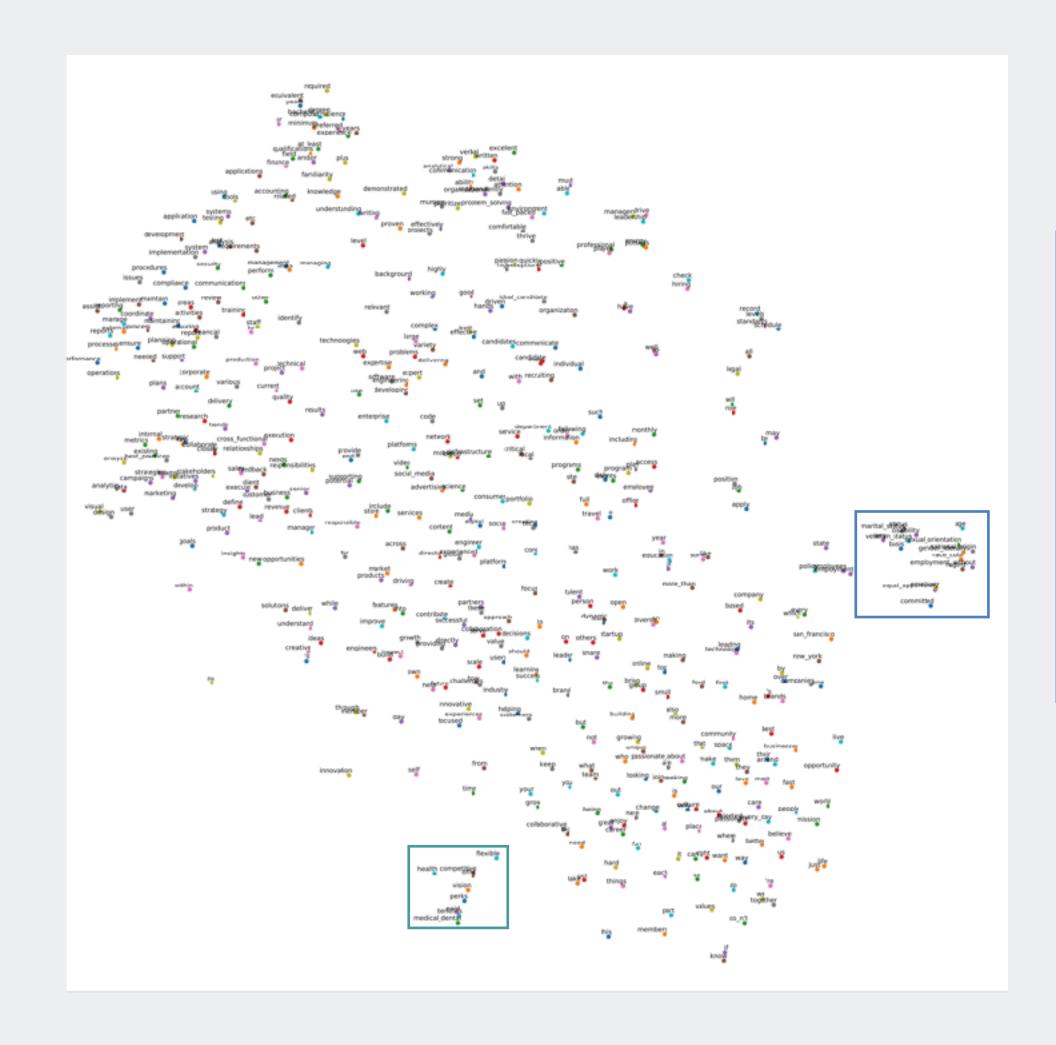
Language Modeling

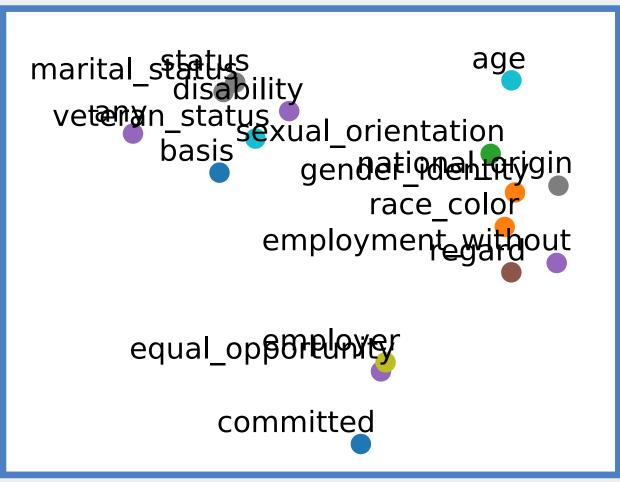
Different word embedding models (GLoVE, word2vec, fastText)

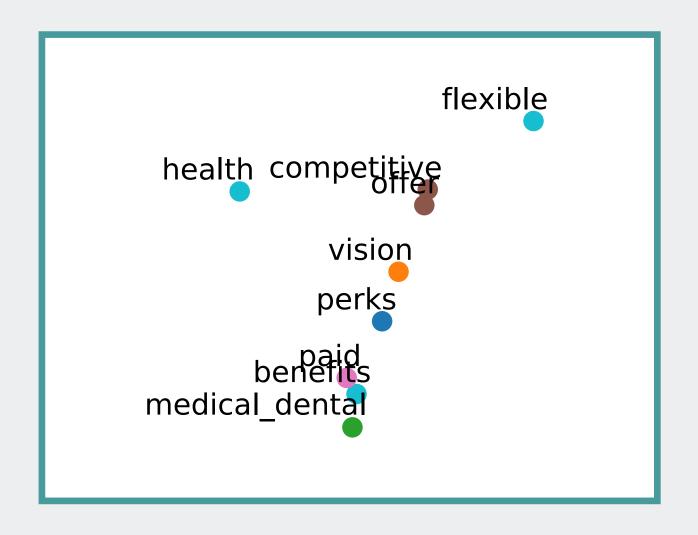


Career language embedding model

Identified equal opportunity and perks language



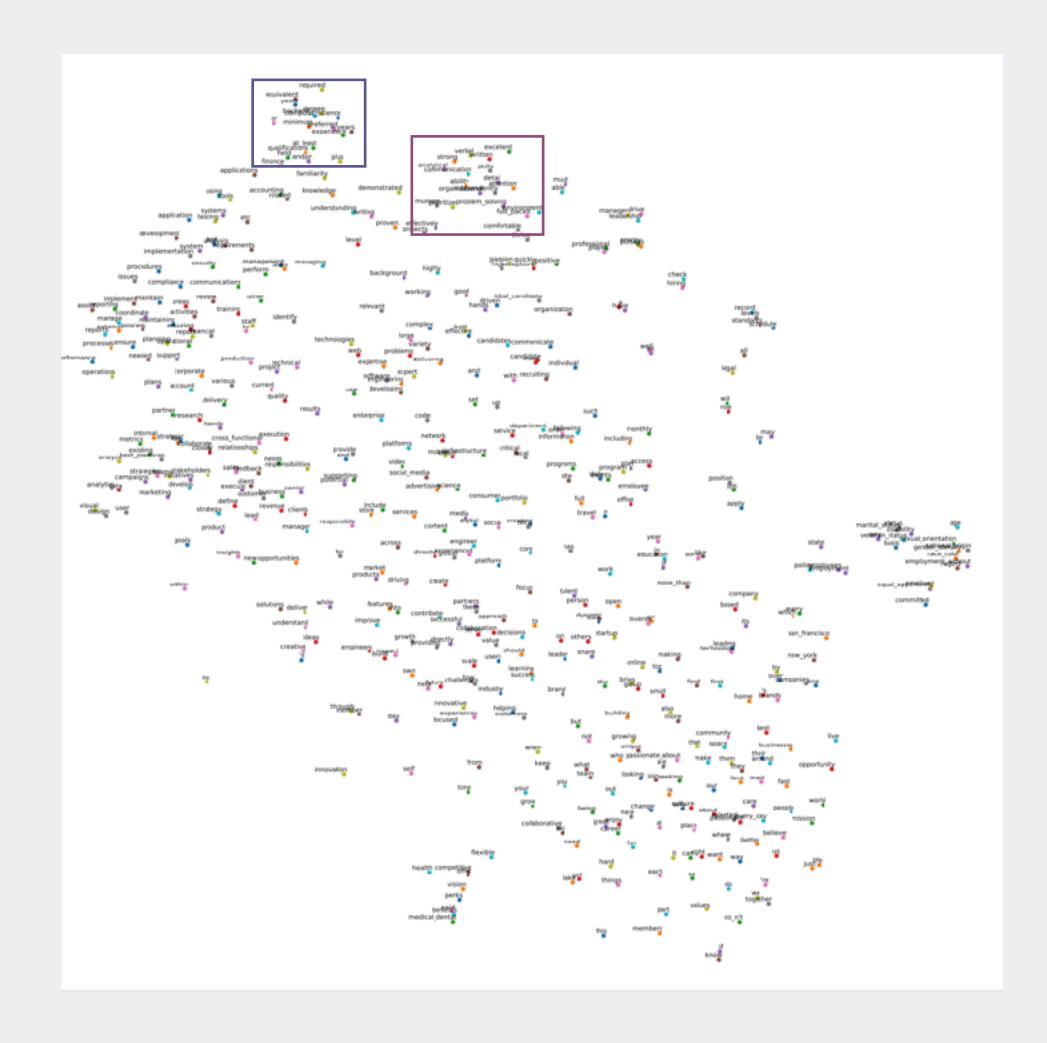




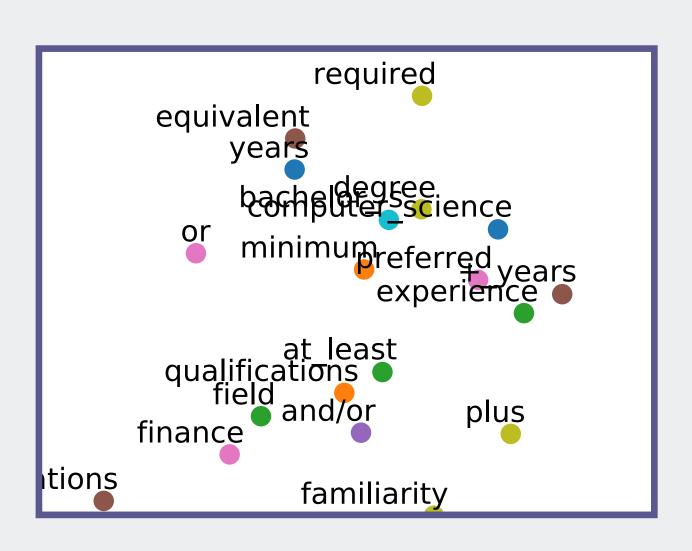


Career language embedding model

Identified 'soft' skills and language around experience



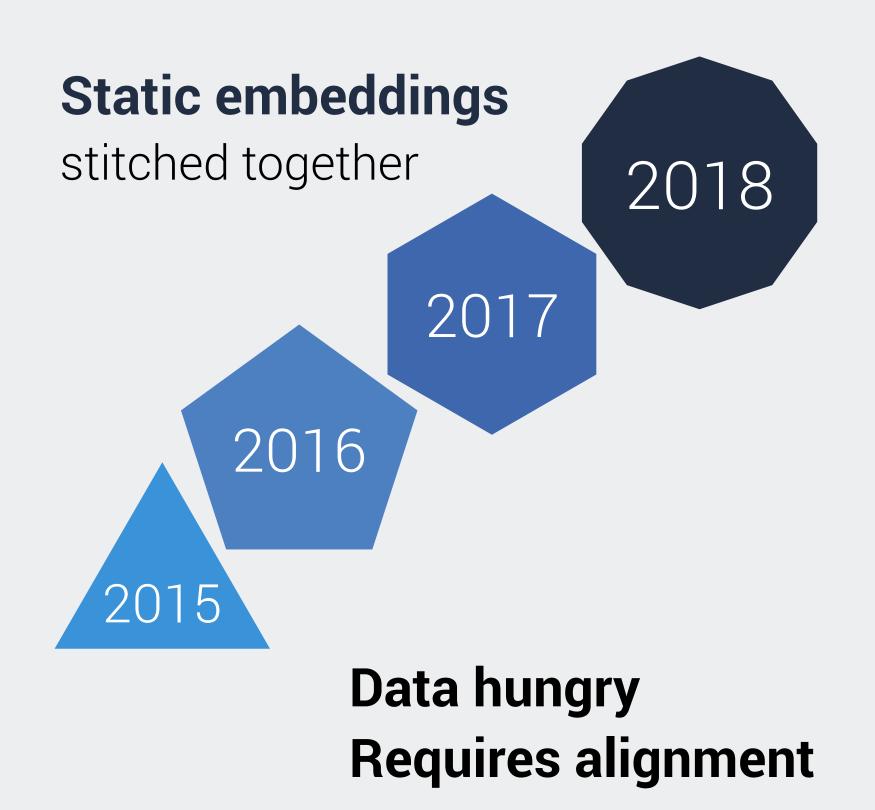




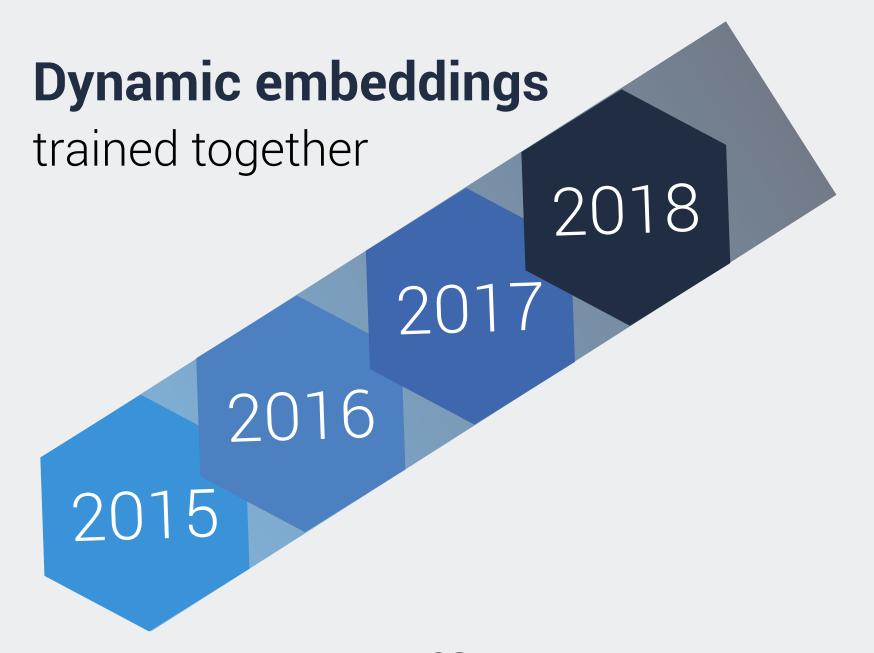


I've got 300 dimensions... but time ain't one

Two approaches to connect embeddings



Kim, Chiu, Kaneki, Hedge and Petrov, <u>arXiv: 1405:3515</u>. Kulkarni, Al-Rfou, Perozzi and Skiena, <u>arXiv: 1411:3315</u>.



Data efficient
Does not require alignment

Balmer and Mandt, <u>arXiv: 1702:08359</u> Yao, Sun, Ding, Rao and Xiong, <u>arXiv: 1703:00607</u>

Rudolph and Blei, arXiv: 1703:08052



Dynamic Bernoulli embeddings

Outputs facilitate quick analysis of trends

Absolute drift

Identifies top words whose usage changes over time course

words with largest drift (Senate)					
IRAQ	3.09	coin	2.39		
tax cuts	2.84	social security	2.38		
health care	2.62	FINE	2.38		
energy	2.55	signal	2.38		
medicare	2.55	program	2.36		
DISCIPLINE	2.44	moves	2.35		
text	2.41	credit	2.34		
VALUES	2.40	UNEMPLOYMENT	2.34		

Embedding neighborhoods

Extract semantic changes by nearest neighbors of drifting words

UNEMPLOYMENT					
1858	1940	2000			
unemployment	unemployment	unemployment			
unemployed	unemployed	jobless			
depression	depression	rate			
acute	alleviating	depression			
deplorable	destitution	forecasts			
alleviating	acute	crate			
destitution	reemployment	upward			
urban	deplorable	lag			
employment	employment	economists			
distressing	distress	predict			



Experiments with dynamic embeddings

	Small Corpus	Large Corpus
Job Types	All	All
Time Slices	3 (2016-2018)	3 (2016-2018)
Number of Documents	50 k	500 k
Vocabulary Size	10 k	10 k
Data Preprocessing	Basic	Basic
Embedding Dimensions	100 d	100 d



Dynamic embeddings

Small corpus identified gains and losses

Demand for PhDs and MBAs is Falling

PhDs in All Jobs

-23%

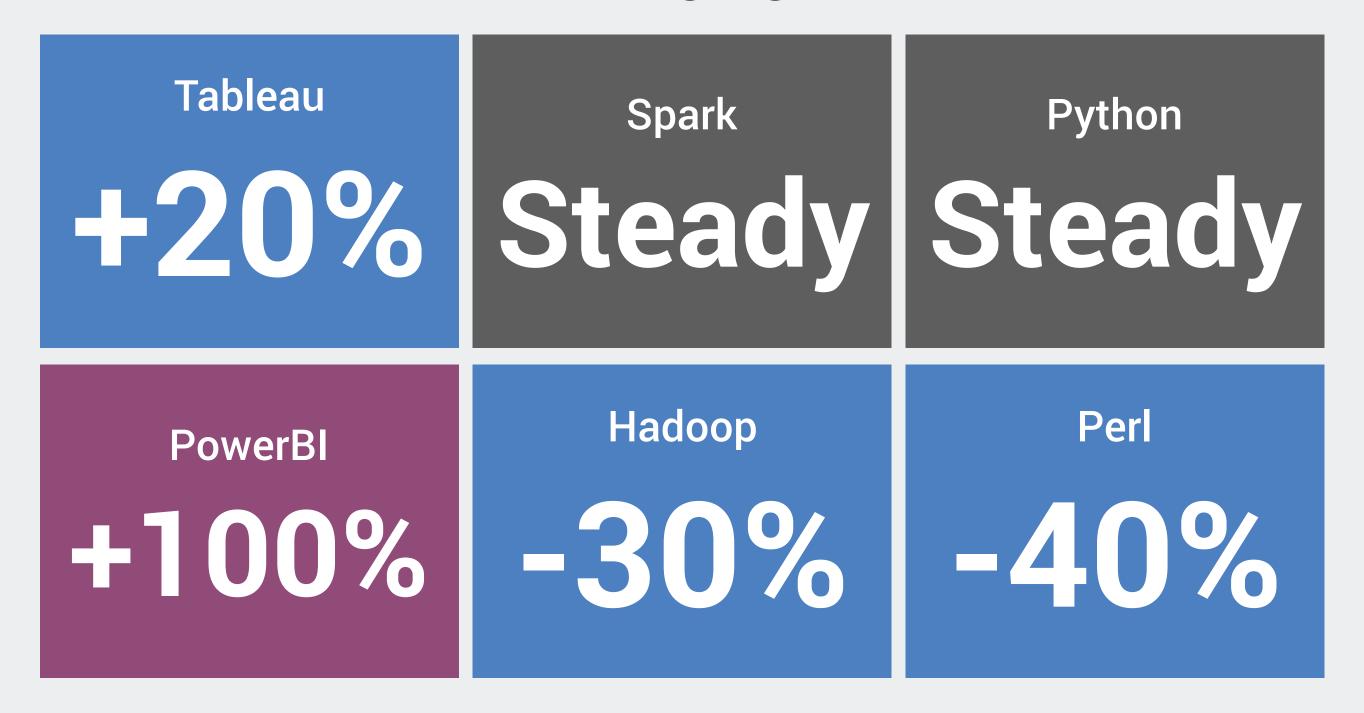
PhDs in DS Jobs

-30%

MBAs in All Jobs

-35%

Data Science skills showing significant shifts



Blue boxes indicate phrases identified from top drifting words analysis.

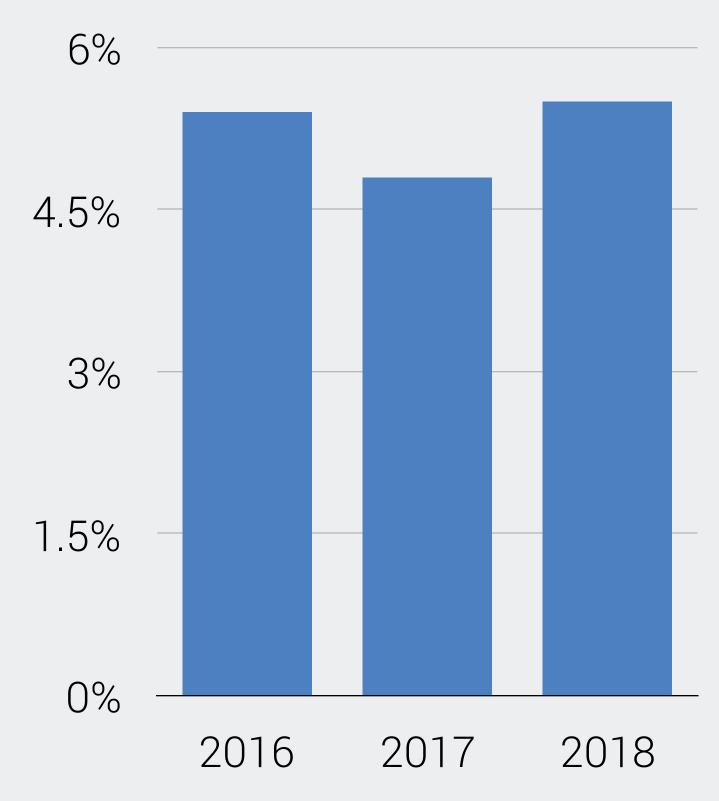
Grey boxes indicate 'control' skills.

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Dynamic embeddings

Large corpus identified role-type dependent shifts in requirements

No change to SQL demand



SQL requirement increases in specific functions



Blue boxes indicate phrases identified from top drifting words analysis.

Grey boxes indicate 'control' skills.

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How have data science skills changed over time?

- Flavors of static word embeddings: The Corpus Issue
- Considerations for developing custom embedding models
- Flavors of dynamic models: Dynamic Bernoulli embeddings

Thank you Women in Analytics!

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